

Morphology Generation for Statistical Machine Translation using Deep Learning Techniques

Marta R. Costa-jussà and Carlos Escolano

TALP Research Center

Universitat Politècnica de Catalunya, Barcelona

marta.ruiz@upc.edu, carlos.escolano@est.fib.upc.edu

Abstract

Morphology unbalanced languages remains a big challenge in the context of machine translation. In this paper, we propose to de-couple machine translation from morphology generation in order to better deal with the problem. We investigate the morphology simplification with a reasonable trade-off between expected gain and generation complexity. For the Chinese-Spanish task, optimum morphological simplification is in gender and number. For this purpose, we design a new classification architecture which, compared to other standard machine learning techniques, obtains the best results. This proposed neural-based architecture consists of several layers: an embedding, a convolutional followed by a recurrent neural network and, finally, ends with sigmoid and softmax layers. We obtain classification results over 98% accuracy in gender classification, over 93% in number classification, and an overall translation improvement of 0.7 METEOR.

1 Introduction

Machine Translation (MT) is evolving from different perspectives. One of the most popular paradigms is still Statistical Machine Translation (SMT), which consists in finding the most probable target sentence given the source sentence using probabilistic models based on co-occurrences. Recently, deep learning techniques applied to natural language processing, speech recognition and image processing and even in MT has reached quite successful results. Early stages of deep learning applied to MT include using neural language modeling for rescoring (Schwenk et al., 2007). Later,

deep learning has been integrated in MT in many different steps (Zhand and Zong, 2015). Nowadays, deep learning has allowed to develop an entire new paradigm, which within one-year of development has achieved state-of-the-art results (Jean et al., 2015) for some language pairs.

In this paper, we are focusing on a challenging translation task, which is Chinese-to-Spanish. This translation task has the characteristic that we are going from an isolated language in terms of morphology (Chinese) to a fusional language (Spanish). This means that for a simple word in Chinese (e.g. 鼓励), the corresponding translation has many different morphology inflexions (e.g. *alentar*, *alienta*, *alentamos*, *alientan* ...), which depend on the context. It is still difficult for MT in general (no matter which paradigm) to extract information from the source context to give the correct translation.

We propose to divide the problem of translation into translation and then a postprocessing of morphology generation. This has been done before, e.g. (Toutanova et al., 2008; Formiga et al., 2013), as we will review in the next section. However, the main contribution of our work is that we are using deep learning techniques in morphology generation. This gives us significant improvements in translation quality.

The rest of the paper is organised as follows. Section 2 describes the related work both in Chinese-Spanish translation and in morphology generation approaches. Section 3 overviews the phrase-based MT approach, which is the one we are using in this paper, together with an explanation of the divide and conquer approach of translating and generating morphology. Section 4 details the architecture of the morphology generation module and it reports the main classification techniques that are used as a key element for the morphology generation step. Section 5 describes

the experimental framework. Section 6 reports and discusses both classification and translation results, which show significant improvements. Finally, section 7 summarises the main conclusions and further work.

2 Related Work

In this section we are reviewing previous related work on morphology generation for MT and on Chinese-Spanish MT approaches.

Morphology generation This approach consists on simplifying the translation task with a target text that has less morphology variation than the original target and then using a postprocessing module to add the proper inflections. For example, (Toutanova et al., 2008) build maximum entropy markov models for inflection prediction of stems. However, most related works are (Giménez and Màrquez, 2004) in which a model is trained to predict each individual fragment of a Part-of-Speech (PoS) tag by means of machine learning algorithms, and (Formiga et al., 2013) use Support Vector Machines (SVMs) to predict verb inflections.

Differently, in this paper, we use deep learning techniques to classify morphology. We are using conclusions from previous work (Costa-jussà, 2015) which shows different simplification techniques for Chinese-to-Spanish and proves that simplification in gender and number have the best trade-off between improving the oracle in translation and keeping the morphology generation complexity at a low level.

Chinese-Spanish There are few works in Chinese-Spanish MT despite being two of the most spoken languages in the world. Most of these works are based on comparing different pivot strategies like standard cascade or pseudo-corpus (Costa-jussà et al., 2012). Also it is important to mention that, in 2008, there were two tasks organised by the popular IWSLT evaluation campaign¹ (International Workshop on Spoken Language Translation) between these two languages (Paul, 2008). The first task was based on a direct translation for Chinese-Spanish. The second task provided corpus in Chinese-English and English-Spanish and asked participants to provide Chinese-Spanish translation through pivot techniques. The second task obtained better

results than direct translation because of the larger corpus provided. Differently, (Costa-jussà and Centelles, 2016) presents the first rule-based MT system for Chinese to Spanish. Authors describe a hybrid method for constructing this system taking advantage of available resources such as parallel corpora that are used to extract dictionaries and lexical and structural transfer rules. Finally, it is worth mentioning that novel successful neural approximations (Jean et al., 2015), already mentioned in the introduction, have not achieved state-of-the-art results for this language pair (Aldón et al., 2016).

3 Machine Translation Architecture

In this section, we review the baseline system which is a standard phrase-based MT system and explain the architecture that we are using by dividing the problem of translation into: morphologically simplified translation and morphology generation.

3.1 Phrase-based MT baseline system

The popular phrase-based MT system (Koehn et al., 2003) focuses on finding the most probable target text given a source text. In the last 20 years, the phrase-based system has dramatically evolved introducing new techniques and modifying the architecture; for example, replacing the noisy-channel for the log-linear model which combines a set of feature functions in the decoder, including the translation and language model, the re-ordering model and the lexical models. There is a widely used open-source software, *Moses* (Koehn et al., 2007), which englobes a large community that helps in the progress of the system. As a consequence, phrase-based MT is a commoditized technology used at the academic and commercial level. However, there are still many challenges to solve, such as morphology generation.

3.2 Divide and conquer MT architecture: simplified translation and morphology generation

Morphology generation is not always achieved in the standard phrase-based system. This may be to the fact that phrase-based MT uses a limited source context information to translate. Therefore, we are proposing to follow a similar strategy to previous works (Toutanova et al., 2008; Formiga et al., 2013), where authors do a first translation

¹<http://iwslt2010.fbk.eu>

from source to a morphology-based simplified target and then, use the morphology generation module that transforms the simplified translation into the full form output.

4 Morphological Generation Module

In order to design the morphology generation module, it is good to know which kind of morphology simplification we are applying to the translation. In this case, as mentioned, we are focusing on the Chinese-to-Spanish task and we are using the conclusions from previous work (Costa-jussà, 2015), where authors compute the oracle of several morphological simplifications. The simplification which achieves the best trade-off among highest translation gain and lowest complexity of morphological generation is the simplification in number and gender. See Table 1 with examples of this simplification.

With these results at hand, we propose an architecture of the morphology generation module that is shown in Figure 2. However, given that we will be using statistical algorithms, this architecture is easily generalizable to other simplification schemes.

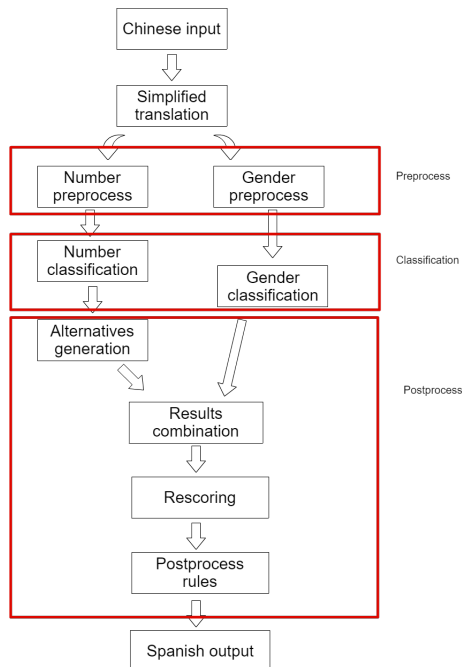


Figure 1: Morphology Generation Architecture

The morphology generation architecture is summarised in the next points and further detailed in the next subsections.

- Feature selection. We have investigated different set of features including information from both source and target languages.
- Classification. We propose a new deep learning classification architecture composed of different layers.
- Postprocess. This consists of generating different alternatives of the classification output and rerank them using a language model. After, we use some rules designed by-hand that allow to solve some specific problems.

This architecture is shown in Figure ??, in which we can see that each of the above processes generates the needed input for the next step. Figure also shows in red the subprocesses that have been developed for these tasks.

4.1 Feature selection

We propose to compare several features for recovering morphological information. Given that both Chinese and simplified Spanish languages do not contain explicit morphology information, we started by simply using windows of words as source of information. We decided to follow Collobert’s approach in which each word is represented by a fixed size window of words in which the central element is the one to classify (Collobert et al., 2011). In our case, we count with the Chinese source text and the simplified Spanish translation. Initially, we designed our system to use exclusively the Chinese text. Then, a second attempt was to use a combination of both Chinese and Spanish by using the alignment file generated during the translation. In this case, we tried two different approaches: (1) use both Chinese and the Spanish window as input; (2) using the Spanish window adding information about its correspondent word in Chinese, i.e. information about pronouns and the number of characters in the word. Finally, we used only the Spanish translation. The main advantage of the latter is that it is not dependant on the alignment file generated during translation.

Our classifiers did not have to train all types of words. Some types of words, such as prepositions (*de*), do not have gender or number. Therefore our system was trained using only determiners, adjectives, verbs, pronouns and nouns which are the ones that present morphology variations in gender

Es_{num}	decidir[VMIP3N0] examinar[VMN0000] el[DA0MN0] c uestión[NCFN000] en[SPS00] el[DA0MN0] período[NCM N000] de[SPS00] sesión[NCFN000] el[DA0MN0] tema[NCMN000] titular [AQ0MN0] “[Fp] cuestión[NCFN000] relativo[AQ0FN0] a[SPS00] el[DA0MN0] derecho[NCMN000] humano[AQ0MN0] “[Fp] .[Fp]
Es_{gen}	decidir[VMIP3S0] examinar[VMN0000] el[DA0GS0] cuestión [NCGS000] en[SPS00] el[DA0GS0] período[NCGS000] de [SPS00] sesión[NCGS000] el[DA0GS0] tema[NCGS000] titular [AQ0GS0] “[Fp] cuestión[NCGS000] relativo[AQ0GS0] a[SPS00] el[DA0GS0] derecho[NCGS000] humano[AQ0GS0] “[Fp] .[Fp]
Es_{numgen}	decidir[VMIP3N0] examinar[VMN0000] el[DA0GN0] cuestión[NCGN000] en[SPS00] el[DA0GN0] período[NCGN000] de[SPS00] sesión[NCGN000] el[DA0GN0] tema[NCGN000] titular [AQ0GN0] “[Fp] cuestión[NCGN000] relativo[AQ0GN0] a[SPS00] el[DA0GN0] derecho[NCGN000] humano[AQ0GN0] “[Fp] .[Fp]
Es	Decide examinar la cuestión en el período de sesiones el tema titulado “ Cuestiones relativas a los derechos humanos ” .

Table 1: Example of Spanish simplification into number, gender and both

or number. However, note that all types of words where used in the windows.

4.2 Classification architecture

We propose to train two different models: one to retrieve gender and another to retrieve number. We inspire our architecture in previous Collobert’s proposal (Collobert et al., 2011) and we modify it by adding a recurrent neural network. This recurrent neural network is relevant because it keeps information about the previous elements in a sequence and, in our classification problem, context words are very relevant. As a recurrent neural network, we use a Long Short Term Memory (LSTM) (Hochreiter and Schmidhuber, 1997) that keeps information about the previous elements in the sequence.

Each model classifies three different classes. The gender model classifies every word as masculine (M), feminine (F) and neutral(N). As does the number model with singular (S), plural (P) and neutral (N) words.

Figure 2 shows an overview of the different layers involved in the final classification architecture, which are detailed as follows:

- **Embedding layer** We represent each word as its index in the vocabulary, i.e. every word is represented as only one discrete value. The embedding layer represents our data in a higher dimensionality continuous space and it becomes the first layer of our architecture. After this process, each word is represented as a numeric array and each window is a matrix.
- **Convolutional layer** At this point, we have a representation that is suitable to be classified using the recurrent neural network, but in order to improve performance we add an additional step by using a convolutional neural network. This step allows the system to de-

tect some common patterns between the different words.

- **LSTM Layer** The importance of this layer is its ability to maintain information of a sequence but also its ability to forget when the information stored is no longer useful. An example of this is the case of punctuation marks. When a punctuation mark is encountered in the text, the following words are not depending on the words before.
- **Sigmoid layer:** This layer helps to smooth the results obtained by the previous layer and compress the results to the interval $[-1, 1]$.
- **Softmax layer:** Finally, this layer allows to show the results of the model as probabilities by ensuring that the returned value of each class is found at the interval $[0, 1]$ and the sum of all classes equals 1.

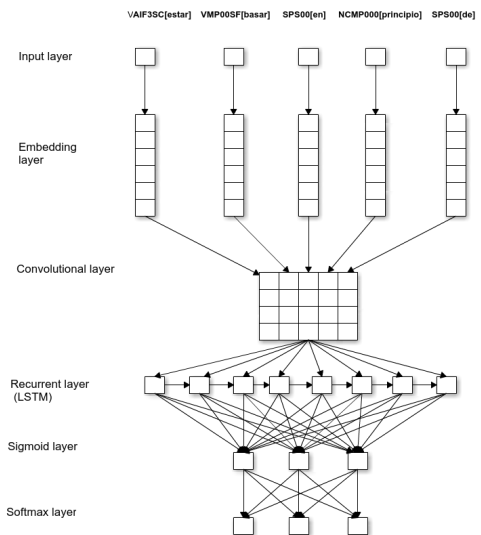


Figure 2: Neural network overview

To generate the above architecture we used the library *keras* (Chollet, 2015) for creating and ensembling the different layers. Using NVIDIA

GTX Titan X GPUs with 12GB of memory and 3072 CUDA Cores, each classifier proposed had a training time of approximately 1h and 12h for the small and large corpus, respectively.

4.3 Postprocess

At this point in the pipeline, we have two models (gender and number) that allow us to reintroduce the morphological information to the translated words. Next step is generating the full Part-of-Speech (PoS) tag to obtain the correct word form. For this purpose, we use the vocabulary and conjugations rules provided by *Freeling* (Padró and Stanilovsky, 2012) based on the lemma and PoS tag.

Before generating the final tag and in order to boost the performance of our system, we add a rescoring step for the weights obtained by the number classification model. To generate the different alternatives, we represent every sentence as a graph (see Figure 3), with the following properties:

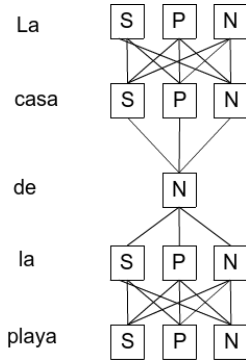


Figure 3: Example of sentence graph. S stands for singular, P for plural and N for neutral

- Each word is represented as a layer of the graph and each node represents a class of the number classification model.
- A node only has edges with all the nodes of the next layer. This way we force the paths in the graph to follow the original structure of the sentence.
- An edge's weight is the probability associated to that possibility by the classification model.
- Each accepted path in the graph starts in the first layer and ends in the last one and because

of its structure is acyclic. This allows us to find the best path in linear time, due to the fact that we only have to visit all layers and pick the node with the greatest weight. The number of elements in a layer can only be 3 if the layer is not classified as neutral, or 1 otherwise, so we can assume it is constant.

We used Yen's algorithm (Yen, 1971) to find the best path, which has an associated cost of $O(KN^2 \log N)$, being K the number of paths to find. With the generated paths we proceed to use *Moses* rescoring tool² in addition with a language model to rescore the probabilities and choose the best option for each sentence, see pseudo code in Algorithm 1.

There are two special cases that the models were not able to treat and we apply specific rules: (1) conjunctions *y* and *o* are replaced by *e* and *u* if they are placed in front of vowels. This could not be generated during translation because both words share the same tag and lemma; (2) verbs with a pronoun as a suffix, *producirse*, second to last syllable stretched (*palabras llanas*) and ending in a vowel are not accentuated. However, after adding the suffix, these words should be accentuated because they become *palabras esdrújulas*, which happen to be always accentuated.

```

Data: G Graph of the sentence, K
Result: best k paths in G
initialization;
A[0] = bestPath(G,0,final);
B = [] ;
i = 0;
for i < K do
  for i in range(0, len(A[K-1])-1) do
    spurNode = A[K-1][i];
    root = A[K-1][0:i];
    for path in A do
      if root = path[0:i] then
        | remove edge(i-1,i) from G;
      end
    end
    for node in root and node != spurNode do
      | removes node node from G;
    end
    spurPath = bestPath(G,spurNode, final) totalPath = root +
    spurPath;
    B.append(totalPath);
    restore edges from G;
    restore nodes from G;
    if B is empty then
      | break;
    end
    B.sort();
    A.append(B[0]);
    B.pop();
  end
end

```

Algorithm 1: Pseudo-code implementation for rescoring.

²<https://github.com/mones-smt/monesdecoder/tree/master/scripts/nbest-rescore>

L	Set		S	W	V
ES	Train	Small	58.6K	2.3M	22.5K
		Large	3.0M	51.7M	207.5K
	Development		990	43.4K	5.4k
	Test		1K	44.2K	5.5K
ZH Words	Train	Small	58.6K	1.6M	17.8K
		Large	3.0M	43.9M	373.5K
	Development		990	33K	3.7K
	Test		1K	33.7K	3.8K

Table 2: Corpus Statistics. Number of sentences (S), words (W), vocabulary (V). M stands for millions and K stands for thousands.

5 Experimental framework

In this section, we describe the data used for experimentation together with the corresponding preprocessing. In addition, we detail chosen parameters for the MT system and the classification algorithm.

5.1 Data and preprocessing

One of the main contributions of this work is using the Chinese-Spanish language pair. In the last years, there has appeared more and more resources for this language pair available in (Ziems et al., 2016) or from TAUS corporation³. Therefore, differently from previous works on this language pair, we can test our approach in both a small and large data sets.

- A small training corpus by using the United Nations Corpus (UN) (Rafalovitch and Dale, 2009).
- A large training corpus by using, in addition to the UN corpus, the TAUS corpus, the Bible corpus (Chew et al., 2006) and the BTEC (Basic Traveller Expressions Corpus) (Takezawa, 2006). The TAUS corpus is around 2,890,000 sentences, the Bible corpus about 30,000 sentences and the BTEC corpus about 20,000 sentences.

Corpus statistics are shown in Table 2. Development and test sets are taken from UN corpus.

Corpus preprocessing consisted in tokenization, filtering empty sentences and longer than 50 words, Chinese segmentation by means of the Zh-Seg (Dyer, 2016), Spanish lowercasing, filtering pairs of sentences with more than 10% of non-Chinese characters in the Chinese side and more than 10% of non-Spanish characters in the Spanish

side. Spanish PoS tagging was done using *Freeling*. All chunking or name entity recognition was disabled to preserve the original number of words.

5.2 Parameters details

Moses has been trained using default parameters, which include: grow-diag-final word alignment symmetrization, lexicalized reordering, relative frequencies (conditional and posterior probabilities) with phrase discounting, lexical weights, phrase bonus, accepting phrases up to length 10, 5-gram language model with kneser-ney smoothing, word bonus and MERT optimisation.

About the models created there are several parameters we tuned during the training process. Experimentation has shown that both tasks have different requirements. One parameter to consider is the size of the initial vocabulary, which should keep a trade-off between giving enough information to the system to perform the classification while removing enough words to train the classifier for unknown words. Another parameter is the size of the window. Experimental results had shown that number and gender give the best results for classification using windows of 7 and 9 words respectively. In both cases increasing this size lowers the accuracy of the system. Regarding network layers, a relevant parameter is the size of the resulting embedding. For the current tasks, 128 elements remained stable and increasing further this value augmented the time and hardware cost of training the classifiers. Experimental results shown that the size of the filter in the convolutional layer produced the best results when it was slightly smaller than the window size, being 5 and 7 the best values for gender and number classification respectively. Finally, tuning number of nodes of the LSTM layer increased performance for both classifiers until 70 nodes and then it remained stable with additional ones. Table ?? summarizes these parameters.

Table 3: Values of the different parameters of the classifiers

Parameter	Small		Large	
	Num	Gen	Num	Gen
Window size	9	7	9	7
Vocabulary size	7000	9000	15000	15000
Embedding	128	128	128	128
Filter size	7	5	7	5
LSTM nodes	70	70	70	70

For windows, we only used the simplified Spanish translation. In Table 4 we can see that testing

³<http://www.taus.net>

Table 4: Accuracy of the classifier of number using different sources of information.

Features	Accuracy (%)
Chinese window	72
Spanish window	93.4
Chinese + Spanish window	86

different sources of information with the classifier of number. Adding Chinese had a negative effect in the classifier accuracy.

6 Evaluation

In this section we will discuss the results obtained both in classification and in the final translation task.

Table 5 shows results for the classification task both number and gender and with the different corpus sets. We have contrasted our proposed classification architecture based on neural networks with standard machine learning techniques such as linear, quadratic and sigmoid kernels SVMs (Cortes and Vapnik, 1995) and random forests (Breiman, 2001). All algorithms were tested using features and parameters described in previous sections with the exception of random forests in which we added the one hot encoding representation of the words to the features.

We observe that our proposed architecture achieves by large the best results in all tasks. It is also remarkable that the accuracy is lower using the bigger corpus, this is due to the fact that the small set consisted in texts of the same domain and the vocabulary had a better representation of specific words such as country names.

Table 5: Classification results. In bold, best results. Num stands for Number and Gen, for Gender

Algorithm	Small		Large	
	Num	Gen	Num	Gen
Naive Bayes	61.3	53.5	61.3	53.5
Lineal kernel SVM	68.1	71.7	65.8	69.3
Cuadratic kernel SVM	77.8	81.3	77.6	82.7
Sigmoid kernel SVM	83.1	87.4	81.5	84.2
Random Forest	81.6	91.8	77.8	88.1
Neural Network	93.7	98.4	88.9	96.1

Table 6 shows translation results. We show both the Oracle and the result in terms of METEOR (Banerjee and Lavie, 2005). We observe improvement in most cases (when classifying number, gender, both and rescoring), but best results are obtained when classifying number and gender and rescoring number in the large corpus, obtaining a gain up to +0.7 METEOR.

Table 6: METEOR results. In bold, best results. Num stands for Number and Gen, for Gender

Set	System	UN	
		Oracle	Result
Small	Baseline	-	55.29
	+Num	55.60	55.35
	+Gen	55.45	55.39
	+Num&Gen	56.81	55.48
	+Num&Gen +Rescoring(Num&Gen)	-	54.91
	+Num&Gen +Rescoring(Num)	-	55.56
Large	Baseline	-	56.98
	+Num	58.87	57.51
	+Gen	57.56	57.32
	+Num&Gen	62.41	57.13
	+Num&Gen +Rescoring(Num&Gen)	-	56.47
	+Num&Gen Rescoring(Num)	-	57.74

Note that the addition of the rescoring step improves results when applied to number but decreases when both characteristics are combined. This could be caused by the fact that the gender results are better from the classifier output. Also, rescoring may be difficult when balancing two non-normalised features.

7 Conclusions

Chinese-to-Spanish translation task is challenging, specially because of Spanish being morphologically rich compared to Chinese. Main contributions of this paper include correctly de-coupling the translation and morphological generation tasks and proposing a new classification architecture, based on deep learning, for number and gender.

Standard phrase-based MT procedure is changed to first translating into a morphologically simplified target (in terms of number and gender); then, introducing the classification algorithm, based on a new proposed neural network-based architecture, that retrieves the simplified morphology; and composing the final full form by using the standard *Freeling* dictionary.

Results of the proposed neural-network architecture in the classification task compared to standard algorithms (SVM or random forests) are significantly better and results in the translation task achieve up to 0.7 METEOR improvement. As further work, we intend to further simplify morphology and extend the scope of the classification.

Acknowledgements

This work is supported by the 7th Framework Program of the European Commission through the International Outgoing Fellowship Marie Curie Action (IMTraP-2011-29951) and also by the Spanish Ministerio de Economía y Competitividad and

Fondo Europeo de Desarrollo Regional, contract TEC2015-69266-P (MINECO/FEDER, UE).

References

- [Aldón et al.2016] David Aldón, Marta R. Costa-jussà, and José A. R. Fonollosa. 2016. Neural machine translation using bitmap fonts. In *EAMT Workshop on Hybrid Approaches to Translation (HyTRA)*.
- [Banerjee and Lavie2005] Satanjeev Banerjee and Alon Lavie. 2005. Meteor: An automatic metric for mt evaluation with improved correlation with human judgments. In *Proceedings of the acl workshop on intrinsic and extrinsic evaluation measures for machine translation and/or summarization*, volume 29, pages 65–72.
- [Breiman2001] Leo Breiman. 2001. Random forests. *Machine learning*, 45(1):5–32.
- [Chew et al.2006] Peter A Chew, Steve J Verzi, Travis L Bauer, and Jonathan T McClain. 2006. Evaluation Of The Bible As A Resource For Cross-language Information Retrieval. In *Proceedings of the Workshop on Multilingual Language Resources and Interoperability*, pages 68–74.
- [Chollet2015] François Chollet. 2015. Keras, <https://github.com/fchollet/keras>.
- [Collobert et al.2011] Ronan Collobert, Jason Weston, Léon Bottou, Michael Karlen, Koray Kavukcuoglu, and Pavel Kuksa. 2011. Natural language processing (almost) from scratch. *Journal of Machine Learning Research*, 12(Aug):2493–2537.
- [Cortes and Vapnik1995] Corinna Cortes and Vladimir Vapnik. 1995. Support-vector networks. *Machine learning*, 20(3):273–297.
- [Costa-jussà and Centelles2016] Marta R. Costa-jussà and Jordi Centelles. 2016. Description of the chinese-to-spanish rule-based machine translation system developed using a hybrid combination of human annotation and statistical techniques. *ACM Transactions on Asian and Low-Resource Language Information Processing*, 15.
- [Costa-jussà et al.2012] Marta R. Costa-jussà, Carlos A. Henríquez Q., and Rafael E. Banchs. 2012. Evaluating indirect strategies for chinese-spanish statistical machine translation. *Journal Of Artificial Intelligence Research*, 45:762–780.
- [Costa-jussà2015] Marta R. Costa-jussà. 2015. On-going study for enhancing chinese-spanish translation with morphology strategies. In *Proc. of the ACL Workshop on Hybrid Approaches to Translation*, Beijing.
- [Dyer2016] Christopher Dyer. 2016. <http://code.google.com/p/zhseg/>.
- [Formiga et al.2013] Lluís Formiga, Marta R. Costa-jussà, José A. R. Mariño, José B. and Fonollosa, Alberto Barrón-Cedeño, and Lluís Màrquez. 2013. The TALP-UPC phrase-based translation systems for WMT13: System combination with morphology generation, domain adaptation and corpus filtering. In *Proceedings of the Eighth Workshop on Statistical Machine Translation*, pages 134–140, Sofia, Bulgaria, August.
- [Giménez and Màrquez2004] Jesús Giménez and Lluís Màrquez. 2004. Svmtool: A general pos tagger generator based on support vector machines. In *In Proceedings of the 4th International Conference on Language Resources and Evaluation*. Citeseer.
- [Hochreiter and Schmidhuber1997] Sepp Hochreiter and Jürgen Schmidhuber. 1997. Long short-term memory. *Neural computation*, 9(8):1735–1780.
- [Jean et al.2015] Sebastien Jean, Orhan Firat, Kyunghun Cho, Roland Memisevic, and Yoshua Bengio. 2015. Montreal neural machine translation systems for wmt15. In *Proc. of the 10th Workshop on Statistical Machine Translation*, Lisbon.
- [Koehn et al.2003] Philipp Koehn, Franz Joseph Och, and Daniel Marcu. 2003. Statistical Phrase-Based Translation. In *Proc. of the ACL*.
- [Koehn et al.2007] Philipp Koehn, Hieu Hoang, Alexandra Birch, Chris Callison-Burch, Marcello Federico, Nicolas Bertoldi, Brooke Cowan, Wade Shen, Christine Moran, Richard Zens, Chris Dyer, Ondrej Bojar, Alexandra Constantin, and Evan Herbst. 2007. Moses: Open Source Toolkit for Statistical Machine Translation. In *Proc. of the 45th Annual Meeting of the Association for Computational Linguistics*, pages 177–180.
- [Padró and Stanilovsky2012] Lluís Padró and Evgeny Stanilovsky. 2012. Freeling 3.0: Towards wider multilinguality. In *Proceedings of the Language Resources and Evaluation Conference (LREC 2012)*, Istanbul, Turkey, May. ELRA.
- [Paul2008] Michael Paul. 2008. Overview of the iwslt 2008 evaluation campaign. In *Proc. of the International Workshop on Spoken Language Translation*, pages 1–17, Hawaii, USA.
- [Rafalovitch and Dale2009] Alexandre Rafalovitch and Robert Dale. 2009. United Nations General Assembly Resolutions: A Six-Language Parallel Corpus. In *Proc. of the MT Summit XII*, pages 292–299, Ottawa.
- [Schwenk et al.2007] Holger Schwenk, Marta R. Costa-jussà, and José A. R. Fonollosa. 2007. Smooth bilingual ngram translation. In *Proc. of the EMNLP*, Prague.
- [Takezawa2006] Toshiyuki Takezawa. 2006. Multilingual spoken language corpus development for communication research. In *Chinese Spoken Language Processing, 5th International Symposium, ISCSLP*

- 2006, Singapore, December 13-16, 2006, *Proceedings*, pages 781–791.
- [Toutanova et al.2008] Kristina Toutanova, Hisami Suzuki, and Achim Ruopp. 2008. Applying morphology generation models to machine translation. In *Proc. of the conference of the Association for Computational Linguistics and Human Language Technology (ACL-HLT)*, pages 514–522, Columbus, Ohio.
- [Yen1971] Jin Y Yen. 1971. Finding the k shortest loopless paths in a network. *management Science*, 17(11):712–716.
- [Zhand and Zong2015] Jiajun Zhand and Chengqing Zong. 2015. Deep neural networks in machine translation: An overview. *IEEE Intelligent Systems*, pages 1541–1672.
- [Ziems et al.2016] Michał Ziems, Marcin Junczyk-Dowmunt, and Bruno Pouliquen. 2016. The united nations parallel corpus v1.0. In *Proceedings of the Tenth International Conference on Language Resources and Evaluation (LREC 2016)*, may.